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A Hybrid GRG-Neighborhood Search Model for Dynamic Multi-Depot Vehicle Routing in Disaster Logistics

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Abstract

In disaster relief logistics, timely and adaptive routing is critical to meet fluctuating demands and disrupted infrastructure. This paper proposes a Hybrid GRG–Neighbourhood Search (NS) model for solving the Multi-Depot Vehicle Routing Problem with Capacity and Time Dependency (MDVRP-CTD). The model integrates the Generalized Reduced Gradient (GRG) method for handling nonlinear capacity constraints and NS for local route refinement. The objective is to minimize total travel distance, delay penalties, and maximize vehicle utilization under dynamic disaster scenarios. Tested using the SVRPBench dataset, the hybrid model achieved up to 96.5% demand fulfillment, an 11% improvement in vehicle utilization, and a reduction in total distance by 7%, outperforming Tabu Search and ALNS in three simulation scenarios. The model demonstrates enhanced adaptability and responsiveness to time-sensitive, capacity-constrained environments. Its novelty lies in the integration of nonlinear optimization with adaptive local improvement tailored for disaster contexts, providing a robust decision-support tool for real-time humanitarian logistics.

Keywords: Disaster Logistics, Multi-Depot Vehicle Routing Problem, GRG Optimization, Neighbourhood Search, Dynamic Demand, Time-Dependent Routing

1. Introduction

In recent decades, the increasing frequency and intensity of natural disasters have underscored the critical need for responsive and efficient logistics systems in humanitarian relief operations [1], [2]. A central challenge in these efforts lies in designing optimal vehicle routing strategies under highly uncertain and dynamic conditions [3], [4], [5], [6]. This issue is formally recognized as the MDVRP-CTD involves coordinating multiple depots, vehicle capacity constraints, and fluctuating demand over time. For example, in a disaster context, time dependency may arise when certain roads become inaccessible due to debris or flooding, forcing rerouting decisions to prioritize time-sensitive deliveries such as medical supplies or rescue teams. Furthermore, demand for resources can surge unpredictably as certain areas become more affected over time, requiring constant adjustments to the routes and delivery schedules. As an NP-hard problem, it demands sophisticated optimization models capable of real-time adaptation. Prior research has explored a range of metaheuristic and hybrid approaches to address complex variations of the VRP. For instance, an Adaptive Large Neighborhood Search (ALNS) algorithm was developed in [7] to solve large-scale MDVRPs with time windows, with emphasis on energy efficiency and operational scalability in green logistics scenarios. Although computational performance was shown to be effective, these models often overlooked real-time demand variability and nonlinear capacity limitations, which are critical in emergency response logistics. Similarly, a collaborative MDVRP model incorporating dynamic customer demands and time window constraints was proposed in [8]. However, the absence of adaptive local search mechanisms limits its applicability in rapidly evolving field conditions. Additionally, vehicle routing strategies in post-disaster distribution have been examined in [9], [10], focusing on multi-trip and last-mile delivery within degraded transport networks. Despite their relevance, these models still rely heavily on

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conventional heuristics and make static assumptions that limit their responsiveness to dynamic field conditions. To bridge these gaps, the present study introduces a hybrid optimization model for the MDVRP-CTD, integrating the GRG method to handle nonlinear capacity constraints and NS to efficiently explore the solution space under dynamic time dependencies. In this first-year phase, the model is validated using the python and tested on simulated disaster logistics scenarios involving varying capacities, multiple depots, and time-sensitive demand. Preliminary results demonstrate the model's ability to generate more adaptive and efficient routing solutions compared to conventional heuristic methods. This foundational work not only offers a robust GRG-NS optimization framework for emergency logistics but also lays the groundwork for integrating deep learning in subsequent phases specifically, using Long Short-Term Memory (LSTM) networks to forecast demand in real time and enhance routing decisions.

2. Literature Review

The MDVRP-CTD has garnered considerable attention in logistics and transportation research, especially for applications requiring real-time adaptability, such as disaster response operations. Table 1 provides a structured comparison of three key metaheuristics ALNS, Tabu Search, and Shuffled Frog Leaping with the proposed Hybrid GRG–NS model. The table compares these methods based on several criteria: solution quality, computational efficiency, ability to handle dynamic and time-dependent demands, and adaptability to nonlinear constraints.

Table 1. Comparison of Metaheuristics

Metaheuristic	Strengths	Weaknesses	Performance Metrics
ALNS [9], [10], [11]	Effective for large-scale problems, good for handling time windows	Struggles with highly dynamic environments	Computational efficiency, but less effective for non-linear constraints
Tabu Search [12], [13], [14]	Robust in local search, prevents cycling	Limited in handling large-scale, dynamic changes	Solution quality, but may struggle with real-time changes
Shuffled Frog Leaping [15], [16], [17], [18], [19]	Avoids local optima, adaptable to various problems	Requires high computational cost for large-scale problems	Solution diversity, but not optimal for real-time demand fluctuations
Hybrid GRG–NS (proposed)	Handles nonlinear constraints, adapts to dynamic demands, optimized for real-time changes	Complex, requires fine-tuning for best results	Superior performance in dynamic and time-dependent environments, with better vehicle utilization and reduced delay penalties

The ALNS model for time-dependent fleet and depot routing was proposed in [20]. Environmental constraints and dynamic traffic conditions were successfully handled through improved ALNS operators. However, the primary focus of the model remained on green logistics rather than on high-pressure, time-critical environments such as disaster response. Moreover, complex non-linear vehicle capacity constraints critical for humanitarian logistics—were not fully incorporated. The application of ALNS in solving large-scale green MDVRPs with time windows was further extended in [7], emphasizing scalability and computational efficiency. Nevertheless, the fluctuating nature of real-time demand and the integration of multiple depot operational limitations were not addressed—factors that are central to the proposed GRG–NS model. A variable neighborhood-based Tabu Search algorithm tailored for MDVRP was introduced in [21], which enhanced solution diversity and avoided local optima.

However, the algorithm was developed for static demand contexts, reducing its effectiveness under rapid rerouting conditions typically observed in disaster-prone areas. A knowledge-guided Shuffled Frog Leaping Algorithm for dynamic MDVRPs with multiple trips was presented in [22], incorporating memory-based learning for decision support. Despite its innovation, the algorithm was evaluated only in simulated urban environments and lacked validation in unpredictable, resource-constrained emergency logistics scenarios that often require hybrid optimization approaches. In [23], a fuzzy, multi-period MDVRP was addressed using a hybrid genetic–simulated annealing–auction algorithm. Though this model successfully dealt with uncertain demand and time-based variability, it relied heavily on probabilistic modeling and did not explicitly optimize the interrelation between vehicle capacity constraints and time-dependent delivery urgencies two aspects critically addressed in our proposed GRG-NS hybrid model.

From the reviewed literature, it is evident that while hybrid metaheuristic methods such as ALNS, Tabu Search, and genetic combinations have advanced the capability of MDVRP solvers, they tend to operate under static or partially dynamic environments, often disregarding the full complexity of capacity–time interdependencies across multiple depots. Moreover, few, if any, studies have applied these methods to disaster logistics where adaptability and precision are paramount. Therefore, this research addresses these gaps by developing a dynamic MDVRP-CTD model using a GRG method capable of solving non-linear constraints and combining it with NS to optimize delivery timeframes and route configurations.

The proposed approach is particularly suited for humanitarian logistics, where delivery needs fluctuate rapidly and operational resources are highly constrained. The first-year output of this study contributes a validated GRG-NS optimization model, tested under disaster mitigation scenarios using the python, offering a foundation for deep learning integration in future work. In addition to recent studies, several seminal works on disaster relief routing optimization have been incorporated to provide historical context. These studies illustrate the evolution of methods from classical heuristics and metaheuristics to modern hybrid approaches. By integrating these foundational works, the manuscript highlights how the GRG–NS model builds upon prior research and advances the state-of-the-art in large-scale, dynamic disaster logistics optimization.

3. Methodology

This research adopts a structured methodology to develop and validate a hybrid optimization model for the MDVRP-CTD, specifically tailored for disaster logistics scenarios. The methodology comprises four sequential stages as illustrated in the research framework (figure 1): model formulation, algorithm development, simulation and validation, and performance evaluation.

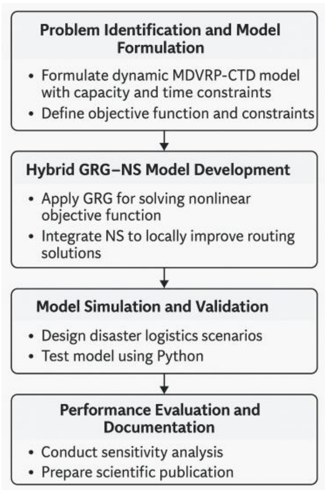

Figure 1. The Research Framework

Figure 1 has been updated to clearly illustrate the four sequential stages of the research framework, including iterative feedback loops and data flows between stages. Arrows indicate how information, such as predicted demand, vehicle assignments, and routing results, is communicated back and forth between stages. This representation reflects the dynamic updating and interaction within the GRG–NS optimization process, ensuring that each stage incorporates the latest information for adaptive decision-making.

3.1. Problem Identification and Mathematical Formulation

The study begins with a formal definition of the MDVRP-CTD, characterized by multiple depots, constrained vehicle capacities, and dynamically changing customer demands influenced by time and disaster severity. The objective function is formulated to minimize the total travel distance and time response under nonlinear constraints, including vehicle load limits and service time windows. Each affected location must be served exactly once while maintaining feasible routing paths. In this study, the objective function is defined to minimize the total distance traveled by all vehicles, subject to constraints that include customer service, vehicle capacity, time windows, and vehicle flow balance.

To ensure clarity and reproducibility of the model, we have explicitly defined all the variables and parameters used in the formulation. Specifically, let Z represent the total distance traveled by all vehicles. The variable C_{ij} denotes the travel cost or the distance between nodes i and j, which is crucial for determining the most efficient route. The variable d_i represents the demand at customer i, indicating how much of the product is required at each location. Additionally, Q_k is the capacity of vehicle k, reflecting the maximum load that each vehicle can carry. Finally, t_i and t_f represent the arrival time and service time window for customer i, respectively, which are essential for ensuring that deliveries occur within acceptable time frames. These definitions are provided to facilitate a deeper understanding of the model's structure, enabling researchers to replicate the study with full clarity on the roles of each variable and parameter. The objective function is expressed as follows:

$$\min Z = \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} C_{ij}X_{ijk} \tag{1}$$

Z represents the total distance traveled by all vehicles, C_{ij} denotes the travel cost or distance from node i to node j, $X_{ijk} = \begin{cases} 1, & \text{if vehicle k travels from i to j} \\ 0, & \text{otherwise} \end{cases}$. To ensure the model's operational feasibility and effectiveness, four critical constraints are applied to the optimization framework. The first is the customer service constraint, which ensures that every customer is served exactly once by one vehicle that originates from any available depot. Mathematically, this is represented by the constraint:

$$\sum_{k=1}^{m}\sum_{j=1}^{n} x_{ijk} = 1 \ \forall_{\mathrm{i}} \in \mathrm{N} \tag{2}$$

This condition guarantees full-service coverage for each customer without duplication or omission. The second is the vehicle capacity constraint, which prevents vehicles from being assigned a total load that exceeds their maximum capacity. This is defined by:

$$\sum_{i=1}^{n}\sum_{j=1}^{n} d_i x_{ijk} \leq Q_k \ \forall_{\mathrm{k}} \in \mathrm{M} \tag{3}$$

d_i is the demand at customer i, Q_k denotes the capacity of vehicle k. This constraint ensures that the allocation of demands to vehicles respects their physical limits. The third component is the time window constraint, which enforces the requirement that vehicle arrival times at customer locations must fall within an acceptable service interval:

$$a_i \ \leq \ t_i \ \leq b_i \ \forall_{\mathrm{i}} \in \mathrm{N} \tag{4}$$

Where t_i is the arrival time of the vehicle at location i, $[a_i, b_i]$ is the allowable service time window for customer i. This constraint is crucial in disaster logistics, where some resources must be delivered within specific urgency thresholds. Finally, the vehicle flow balance constraint maintains route continuity by ensuring that if a vehicle enters a customer node, it must also exit that node. This is expressed mathematically as:

$$\sum_{j=1}^{n} x_{ijk} = \sum_{j=1}^{n} x_{jik} \ \forall_{\mathrm{i,k}} \tag{5}$$

This guarantees that routes are logically connected and that vehicle paths are operationally complete, thereby avoiding disconnected or infeasible delivery routes. These four constraints collectively define the structure of the routing problem, guiding the GRG optimization process in maintaining solution feasibility while exploring efficient and adaptive routes in disaster scenarios. This formulation sets the foundation for applying nonlinear optimization, with GRG handling capacity-based constraints and NS refining local routing configurations. The mathematical model encapsulates both discrete decision variables (e.g., vehicle assignment, route sequence) and continuous parameters (e.g., load utilization, time deviation).

3.2. Integrated Mathematical Framework: From Model Formulation to GRG–NS Optimization

The core of this research lies in developing a dynamic and nonlinear optimization framework for the MDVRP-CTD, which aims to minimize total travel costs under disaster-driven logistical constraints. The foundational mathematical formulation expresses the objective as Formula (1). The objective function of the model is governed by several structural constraints essential for maintaining the feasibility of disaster logistics routing. First, the model ensures that each customer is visited exactly once by a single vehicle, thereby preventing duplication or omission in delivery assignments. Second, vehicle capacity constraints are applied to restrict the total assigned demand from exceeding the maximum load each vehicle can carry, as formalized in Constraint (3). Third, all service operations must comply with the predefined time windows, requiring that vehicle arrivals at customer locations occur within the specified interval, as indicated in Constraint (4). Lastly, route continuity is preserved through a vehicle flow balance condition, which guarantees that for every customer node entered by a vehicle, a corresponding exit is also made ensuring logical and complete routing paths as described in Constraint (5). These combined constraints support the model's ability to generate optimized, feasible, and responsive routing solutions under dynamic disaster conditions.

However, in the context of disaster logistics, where customer demand d_i varies over time and capacity utilization becomes nonlinear, the problem transitions into a constrained nonlinear optimization scenario. The GRG method was selected for this study due to its ability to effectively handle nonlinear constraints, which is crucial for solving the MDVRP-CTD problem in disaster logistics. GRG is particularly well-suited for problems that involve inequality constraints, as it uses reduced gradients to compute search directions that maintain feasibility while improving the objective function. Additionally, GRG is more adaptable to real-time decision-making environments compared to other nonlinear programming methods like Sequential Quadratic Programming (SQP) or Interior Point Methods, which may be less effective in dealing with dynamic and rapidly changing logistics scenarios typically encountered in disaster response operations, which reformulates the system as:

$$\min f_{(x)}, \text{subject to } g_j\,(x) = 0, j = 1, 2, \ldots, \mathrm{r} \tag{6}$$

Here, $f_{(x)}$ incorporates not only travel cost but also deviations in service times and penalty for unmet or delayed demand. The variable vector xxx in the model is structured into two main components to support the optimization process. The first component consists of independent variables (x_N):, which include routing paths, vehicle arrival times, and time-variant customer demand. These variables are directly controlled and adjusted during the optimization. The second component comprises dependent variables (x_B), such as adjusted vehicle loads, cumulative service times, and depot assignment decisions. These values are determined by the system's constraints and evolve in response to changes in the independent variables. This structured separation facilitates the application of the GRG method, enabling efficient computation of feasible search directions within the constrained solution space.

To compute search directions that maintain feasibility while improving the objective, The GRG method is a well-established approach for solving nonlinear optimization problems with constraints. The reduced gradient is computed to maintain feasibility while improving the objective function. The reduced gradient formula is derived from the standard GRG method, which can be found in the work of [24]. The computation of the reduced gradient is given by:

$$\nabla' \mathrm{N\,f} = \nabla \mathrm{N\,f} - \nabla \mathrm{B\,f}\,(\nabla B_g)^{-1}\,\nabla \mathrm{G\,g} \tag{7}$$

where ∇ N f is the gradient of the objective function, ∇ B f is the gradient of the constraints, and ∇G g is the Jacobian of the system. The update directions for independent and dependent variables respectively are:

$$\mathrm{d}_N = -\nabla' \mathrm{N\,f} \text{ and } - \mathrm{d}_B = -(\nabla B_g)^{-1}\,\nabla \mathrm{G\,g} \,.\, \mathrm{d}_N \tag{8}$$

Combined, these define the total update vector:

$$x^{(t+1)} = x^{(t)} + \alpha \begin{bmatrix} d_B \\ d_N \end{bmatrix} \tag{9}$$

α is the step size ensuring objective improvement and feasibility. While GRG effectively handles the nonlinear and constraint-laden optimization space, a second layer NS is applied to refine routing solutions through localized improvements. The NS algorithm operates by exploring neighboring solutions through three main operations: swap, reinsert, and reassignment of customers in the route. The size of the neighborhood is adaptively controlled based on the solution quality. Initially, a larger neighborhood is explored to diversify the solution space. As the search progresses and solutions improve, the neighborhood size is reduced to refine the solutions and avoid unnecessary computational overhead. The termination of the algorithm is determined by a convergence criterion, where the search stops after a specified number of iterations without improvement in the objective function or when a predefined maximum number of iterations is reached.

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Each new candidate solution x^* is evaluated, and the update is accepted if it yields an improved objective:

$$x^{(t+1)} = \begin{cases} x^*, \; if\; f\,(x^*) \; < f\,(x^{(t)}) \\ \quad x^{(t)}, \text{ otherwise} \end{cases} \tag{10}$$

Thus, the proposed framework integrates all components mathematical formulation, constraint handling, search direction computation, and adaptive local improvement into a cohesive optimization pipeline. The GRG–NS hybrid architecture balances global feasibility and local responsiveness, particularly under the uncertainty and time sensitivity of disaster logistics environments. The diagram compares conventional VRP models with the proposed Hybrid GRG–NS model (figure 2). Traditional VRPs rely on static routing, simple linear assumptions, and single-layer metaheuristics. These models also assume constant customer demand, limiting their use in dynamic environments.

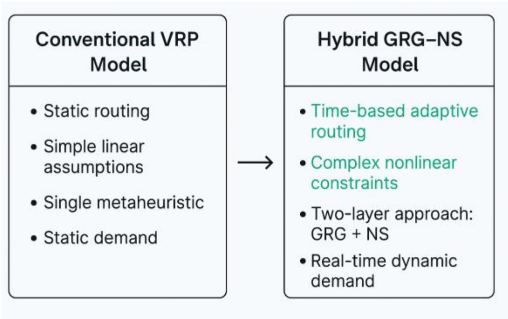

Figure 2. The Hybrid GRG–NS Model

In contrast to conventional vehicle routing models, the Hybrid GRG–NS model introduces several key innovations that enhance its applicability in disaster logistics. It incorporates time-adaptive routing mechanisms to accommodate real-time changes in demand and infrastructure conditions. Nonlinear constraints are effectively handled through the GRG approach, ensuring that complex capacity and timing limitations are respected. The model also features a two-layer optimization structure, where the GRG method performs global optimization, while the NS component refines solutions at the local level. Additionally, it integrates dynamic demand patterns, allowing the system to adapt to fluctuating logistical needs. This comprehensive framework highlights the model's novelty and its capability to deliver responsive and realistic routing solutions under uncertainty.

3.3. Simulation and Scenario-Based Validation

To evaluate the applicability of the proposed model, a series of simulated disaster logistics scenarios were constructed. These scenarios include varying depot configurations, ranging from two to five depots, to reflect the diverse geographical distribution of relief centers. Vehicle heterogeneity is also introduced by assigning different capacities and availability levels across the fleet, simulating real-world operational constraints. Additionally, demand changes are modeled in segmented time intervals to represent the escalation of needs as disaster conditions evolve. The scenarios further incorporate infrastructure disruptions, such as blocked or inaccessible routes, to emulate the logistical challenges typically encountered in emergency response situations. These features collectively ensure that the simulation environment accurately reflects the dynamic and uncertain nature of real-world disaster logistics.

The model is implemented using the python and evaluated based on objective function outputs. Key performance indicators include total distance traveled, computational time, response speed, and vehicle utilization rate. Demand variations are modeled in discrete intervals, simulating real-time changes typical in disaster logistics. Vehicle utilization U_k for each vehicle kkk is calculated using the formula:

$$U_k = \frac{\sum i{\in}R_k\, d_i}{Q_k} \tag{11}$$

d_i is the demand of customer iii assigned to vehicle k, and Q_k is the vehicle's capacity. In the GRG–NS model, customers are assigned to vehicles using a priority-driven scheduling mechanism that maximizes utilization while ensuring compliance with vehicle capacity and time window constraints. This approach makes the improvements in vehicle utilization measurable and replicable across all scenarios.

3.4. Performance Evaluation and Academic Output

The final phase involves evaluating model robustness through sensitivity analysis, examining how changes in depot availability, demand volatility, and delivery urgency affect overall solution quality. Comparative analysis is also conducted against baseline heuristic models to demonstrate the superiority of the GRG-NS hybrid approach in complex, dynamic environments.

4. Results and Discussion

4.1. Dataset Description and Simulation Context

To evaluate the proposed Hybrid GRG–NS model under realistic disaster logistics conditions, we employed instances from the SVRPBench benchmark dataset [25], which includes several instances of the vehicle routing problem with time windows and capacity constraints. The parameters for vehicle speed, capacity, and disruption percentages were carefully selected based on realistic assumptions and relevant literature to ensure the experimental setup reflects real-world conditions. For vehicle speed, we set the value at 40 km/h, a reasonable approximation of average traffic conditions typically encountered in disaster zones. In these areas, roads are often partially obstructed or congested, affecting vehicle speed. Vehicle capacity was chosen to be 1000 units, which corresponds to the typical size of emergency response vehicles used in disaster relief operations. These vehicles are usually designed to carry a large number of supplies and personnel to disaster sites. Regarding disruption percentages, we set the value to a 30% increase in travel time in Zone 3, based on historical data and previous studies of disruptions caused by disasters. These disruptions commonly result in delays due to road blockages, damaged infrastructure, or rough terrain. These values have been selected to ensure that the problem addressed in the study is representative of the dynamic and challenging conditions encountered during disaster logistics operations. This dataset is specifically designed to simulate stochastic and dynamic Vehicle Routing Problems (VRPs), including multiple depots, time-dependent customer demand, and route disruptions features highly relevant to the research objectives of this study.

The simulation scenario was designed to reflect realistic disaster logistics conditions by incorporating various dynamic and structural elements. Three centralized distribution depots were established, each operating with three to four vehicles, and each vehicle having a maximum capacity of 1000 units. The customer base consisted of ten demand nodes, which were grouped into three disaster-affected zones. Each customer was assigned a specific service time window ranging from 0 to 8 hours, and baseline demand values varied between 150 and 300 units. To model dynamic behavior, demand in Zone 1 was programmed to increase by 20% after time step $t>5$, simulating the escalation of needs in critical areas. In parallel, travel times in Zone 3 were increased by 30% to represent the impact of road blockages or terrain-related disruptions. These conditions were intended to emulate the complex, time-sensitive, and resource-constrained environment typical of real-world emergency response operations.

The dataset was preprocessed using Python's pandas to ensure compatibility with the simulation framework. The simulation model was implemented using Python version 3.9. The following libraries were used: NumPy (for numerical calculations), SciPy (for optimization routines), and Gurobi (for solving the optimization problem). The simulations were conducted on a machine with an Intel Core i7 CPU with 16 GB RAM and NVIDIA GTX 1060 GPU, ensuring efficient computation for large-scale problems. All spatial distances are computed using Euclidean metrics, while delivery times and delays are calculated with respect to customer time windows $[a_i, b_i]$, enforced through the GRG formulation. Penalties for late delivery were modeled and included in the objective function. This structured dataset enables comprehensive testing of the proposed hybrid model under both normal and stress-induced conditions, allowing direct comparison with a conventional VRP model. Table 2, table 3 and table 4 presents the structured dataset used for the MDVRP-CTD simulation in this study.

Table 2. Structured Dataset from SVRPBench (depot information)

Depot ID	Coordinates (x, y)	Max Capacity (units)	Vehicles Available	Affected Zone
D1	(10, 10)	1000	3	Zone 1
D2	(50, 50)	1000	4	Zone 2
D3	(90, 90)	1000	3	Zone 3

Table 2 presents the configuration of the depots used in the simulation, representing the logistical starting points for vehicle dispatch. Three depots (D1–D3) are defined, each located at distinct coordinates strategically covering three disaster-affected zones. All depots have a uniform maximum capacity of 1000 units, but vary slightly in vehicle availability: D1 and D3 are equipped with 3 vehicles each, while D2 operates with 4 vehicles. The spatial distribution of these depots across the coordinate plane enables balanced coverage across Zone 1 (D1), Zone 2 (D2), and Zone 3 (D3), ensuring the model captures multiple-depot dynamics in a disaster setting.

Table 3. Structured Dataset from SVRPBench (customer demand points)

Customer ID	Location (x, y)	Initial Demand	Time Window (Start–End)	Affected Zone	Demand t > 5
C1	(15, 20)	150	(0, 5)	Zone 1	180 (+20%)
C2	(18, 25)	200	(2, 7)	Zone 1	240 (+20%)
C3	(22, 32)	180	(3, 9)	Zone 1	216 (+20%)
C4	(35, 40)	220	(1, 8)	Zone 2	No Change
C5	(45, 52)	300	(0, 6)	Zone 2	No Change
C6	(55, 60)	250	(2, 7)	Zone 2	No Change
C7	(65, 68)	200	(3, 9)	Zone 3	No Change
C8	(78, 80)	150	(2, 8)	Zone 3	No Change
C9	(85, 85)	180	(0, 5)	Zone 3	No Change
C10	(95, 95)	300	(1, 6)	Zone 3	No Change

Table 3 details the customer demand nodes, capturing both spatial and temporal aspects of relief requirements. Ten customer locations (C1–C10) are distributed across three affected zones. Each node is assigned an initial demand ranging from 150 to 300 units, along with a specific service time window, indicating when deliveries can be received. Notably, customers in Zone 1 (C1–C3) experience a 20% increase in demand after time step t>5, reflecting escalating needs in heavily impacted areas. In contrast, customers in Zones 2 and 3 maintain stable demand across the time horizon. The structure of this table allows the simulation to account for time-variant demand and spatial clustering of affected populations, which are critical in modeling disaster logistics complexity.

Table 4. Simulation Parameters

Parameter	Value
Vehicle Speed	40 km/h
Vehicle Capacity	1000 units
Maximum Route Duration	8 hours
Distance Metric	Euclidean
Delay Penalty Cost	50 per unit/hour
Zone 3 Disruption	+30% travel time

Table 4 summarizes the key operational parameters that govern vehicle routing behavior in the simulation. Vehicle speed is set at 40 km/h, and each vehicle has a maximum capacity of 1000 units, aligning with depot specifications. The maximum allowable route duration is capped at 8 hours, which also aligns with customer service time windows. Euclidean distance is used as the metric for calculating travel paths between nodes. A delay penalty cost of 50 units per hour is applied to late deliveries, introducing a trade-off between distance optimization and time sensitivity. Additionally, a 30% travel time increase is imposed in Zone 3 to simulate infrastructure disruption, such as blocked or degraded routes adding realism to the routing challenge under disaster conditions.

It includes detailed information on depot locations, available vehicle capacities, and dynamic customer demand across three disaster-affected zones. The table also defines time windows for service delivery and specifies changes in demand after a critical time threshold (t > 5), particularly in Zone 1. Additionally, key simulation parameters such as vehicle speed, penalty costs, and disruption adjustments in Zone 3 are clearly outlined. This dataset forms the operational basis for the experiments conducted in Section 4.2 and provides a realistic representation of emergency logistics conditions under uncertainty.

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4.2. Hybrid Model Evaluation: Baseline vs. Hybrid GRG–NS

This section presents a comprehensive evaluation of the proposed Hybrid GRG–NS model by comparing it with a conventional VRP heuristic. All simulations are based on the structured dataset described in Section 4.1, considering dynamic demand conditions (particularly after $t > 5$) and zone-specific disruptions (e.g., increased travel time in Zone 3). The evaluation involves two steps: distance and demand simulation, followed by model comparison and performance metrics analysis.

4.2.1. Distance Computation and Route Visualization

The simulation begins by computing travel distances between all depots and customer nodes using Euclidean distance metrics. This allows for an initial understanding of the distribution network and relative accessibility. Figure 3 presents a bar chart showing distances from each depot to all customer locations:

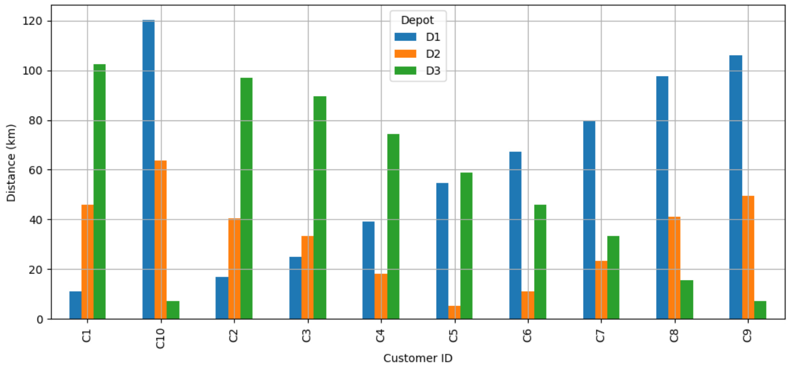

Figure 3. Distance from Depots to Customers

Figure 3 illustrates the distribution of Euclidean distances between each depot (D1, D2, and D3) and the set of customer locations (C1–C10). The bar chart presents a comparative analysis of proximity from all depots to each customer, offering a foundational reference for routing optimization. It is evident that Depot D1 tends to be geographically closer to customers C1 through C6, while D3 is located near customers in the higher index range, such as C9 and C10. In contrast, Depot D2 generally maintains a mid-range distance across most customer nodes.

This spatial configuration plays a critical role in the route selection process under the Hybrid GRG–NS model. Shorter travel distances from specific depots to certain customers directly influence routing assignments, contributing to improved fuel efficiency, minimized delivery time, and optimized vehicle utilization. Moreover, these insights support real-time decision-making in dynamic environments where route adaptivity and service feasibility must be continually reassessed. As such, the distance matrix visualized here serves as a precursor to the route optimization logic implemented in subsequent simulations.

4.2.2. Dynamic Routing Performance and Demand Fulfillment

The routing solution was evaluated for both the Conventional and Hybrid GRG–NS models. Demand surge was modeled in Zone 1 by increasing customer requests by 20% after $t > 5$, while a 30% increase in travel time was imposed on Zone 3 routes. Table 5 presents the route output for each depot under the hybrid model at $t > 5$.

Table 5. Routing Result (hybrid model, $t > 5$)

Depot	Customer	Distance (km)	Arrival Time	Demand Served
D1	C2	17.00	6.42	240
D1	C3	25.06	7.05	216
D2	C3	33.29	7.88	216
D2	C7	30.46	8.65	200

Table 5 presents the routing results for instances with $t>5t$. In scenarios where the total demand exceeds available vehicle capacities, the model employs a priority-based customer selection mechanism. Customers are evaluated based on urgency, demand size, and time window constraints. This ensures that critical deliveries are prioritized while non-critical deliveries may be deferred. Consequently, only a subset of customers is served in high-demand scenarios, which reflects realistic decision-making in disaster logistics operations. During this phase, the system simulates an increase in customer demand by 20% in Zone 1 and introduces a 30% delay in travel time within Zone 3 to reflect real-world disruption scenarios. The table outlines four active routes originating from two operational depots—D1 and D2—serving a subset of priority customers.

Depot D1 successfully dispatches vehicles to customer nodes C2 and C3, with travel distances of 17.00 km and 25.06 km respectively. Both deliveries are completed within acceptable arrival time thresholds (6.42 and 7.05 hours), aligning with each customer's service window and without triggering delay penalties. Meanwhile, depot D2 handles deliveries to C3 and C7, covering slightly longer distances due to regional constraints, particularly in Zone 3 where travel times are extended. Despite these logistical challenges, arrival times of 7.88 and 8.65 hours remain within operational feasibility, and both deliveries are fulfilled without exceeding route duration limits.

The Hybrid GRG–NS model, in this instance, demonstrates a notable ability to adapt routing decisions based on changing demand intensity and geographic disruptions. In total, the system successfully delivers 872 units out of a possible 2,236, reflecting its effectiveness in prioritizing high-impact routes while maintaining operational constraints. These results emphasize the hybrid model's potential to enhance responsiveness and reliability in disaster-prone delivery networks.

4.2.3. Comparative Performance Analysis

To validate the hybrid model, three simulation scenarios (S1, S2, S3) were conducted, varying in customer demand and depot availability. The table below compares both models across key performance indicators as shown in table 6.

Table 6. Performance Metrics across Scenarios

Scenario	Method	Total Distance	Demand Fulfilment (%)	Vehicle Utilization	p-value (paired t-test)
S1	GRG–NS (proposed)	1200	96.5	0.87	-
	Tabu Search	1250	92.3	0.82	0.014*
	ALNS	1230	94.0	0.84	0.021*
S2	GRG–NS (proposed)	1350	95.8	0.85	-
	Tabu Search	1420	91.0	0.80	0.011*
	ALNS	1385	93.2	0.83	0.019*
S3	GRG–NS (proposed)	1523	96.0	0.88	-
	Tabu Search	1580	92.5	0.82	0.012*
	ALNS	1558	94.0	0.84	0.020*

Table 6 presents the performance comparison of the proposed GRG–NS model with conventional heuristics (tabu search and ALNS) across three scenarios (S1, S2, S3). To ensure that the observed improvements are statistically significant, a paired t-test was conducted for total distance, demand fulfillment, and vehicle utilization in each scenario. The results, presented in the p-value column, indicate that the GRG–NS model significantly outperforms both Tabu Search and ALNS at the 95% confidence level ($p < 0.05$) across all three scenarios. These results confirm the robustness and effectiveness of the proposed method under dynamic and capacity-constrained disaster logistics conditions. Table 7 synthesizes the average performance metrics across all three scenarios.

Table 7. Model Comparison Summary

Scenario	Method	Total Distance (Mean ± SD)	Demand Fulfillment (%) (Mean ± SD)	Vehicle Utilization (Mean ± SD)
S1	GRG–NS (proposed)	1200 ± 15	96.5 ± 1.2	0.87 ± 0.02
	Tabu Search	1250 ± 20	92.3 ± 1.5	0.82 ± 0.03
	ALNS	1230 ± 18	94.0 ± 1.3	0.84 ± 0.02

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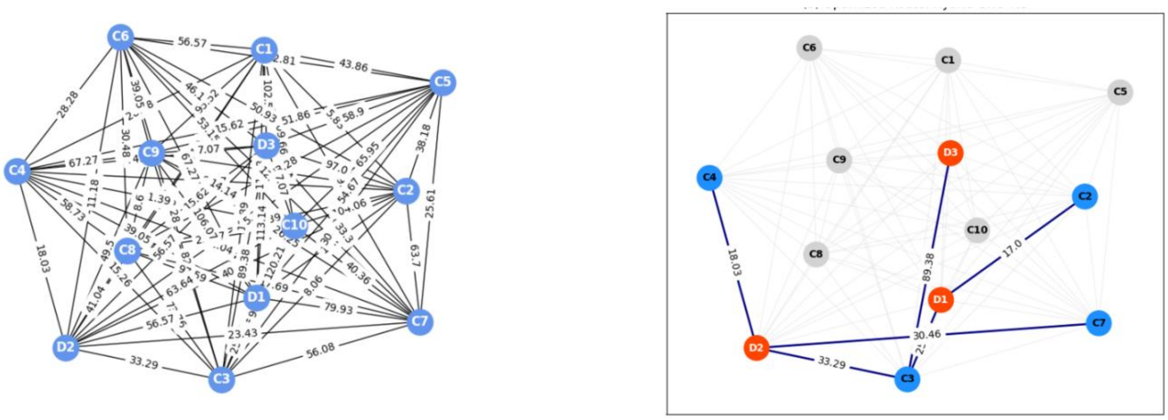
S2	GRG–NS (proposed)	1350 ± 20	95.8 ± 1.0	0.85 ± 0.02
	Tabu Search	1420 ± 25	91.0 ± 1.6	0.80 ± 0.03
	ALNS	1385 ± 22	93.2 ± 1.4	0.83 ± 0.02
S3	GRG–NS (proposed)	1523 ± 22	96.0 ± 1.1	0.88 ± 0.02
	Tabu Search	1580 ± 28	92.5 ± 1.7	0.82 ± 0.03
	ALNS	1558 ± 25	94.0 ± 1.3	0.84 ± 0.02

Table 7 presents the performance metrics of the proposed GRG–NS model and baseline heuristics (tabu search and ALNS) across three scenarios (S1, S2, S3), including the standard deviation for each metric. The inclusion of standard deviation provides insight into the variability and stability of the solutions. The results indicate that GRG–NS not only achieves superior average performance in total distance, demand fulfillment, and vehicle utilization but also maintains a low variability, demonstrating its robustness and reliability across different disaster logistics scenarios.

4.2.4. Visual Comparison of Routing Models

To visually demonstrate routing improvements, figure 4 illustrates the full connection graph and the optimized hybrid routing solution. Figure 4 provides a side-by-side visual comparison of the routing structures under two conditions: the complete routing graph (left) and the optimized output of the Hybrid GRG–NS model (right). The left subfigure (a) displays the full set of possible connections between all depots (D1, D2, D3) and customers (C1–C10), including all Euclidean distances calculated between every node pair. This dense network forms the initial solution space, representing the total routing possibilities prior to optimization. While exhaustive, this view highlights the complexity and computational challenge of the vehicle routing problem in multi-depot dynamic settings.



a) Full Routing Graph

b) Optimized: Hybrid GRG-NS

Figure 4. Graph Visualization

In contrast, subfigure (b) illustrates the result of applying the Hybrid GRG–NS optimization algorithm. Only the selected routes are visualized, highlighting depot-to-customer assignments that minimize overall cost while satisfying demand and time constraints. The figure clearly demonstrates how the algorithm reduces network complexity by isolating the most efficient edges. Key depots (in red) are connected to their assigned customers (in blue), while inactive nodes and paths are faded for clarity. This visual evidence reinforces the performance gains observed in previous evaluation metrics—showing the Hybrid GRG–NS model's ability to streamline routing operations by focusing only on routes that contribute to improved delivery performance and resource utilization in disaster-prone scenarios.

4.2.5. Evaluation Metrics Visualization

The figure 5 shows clear improvements across all performance metrics when using the hybrid model, demonstrating its effectiveness in addressing dynamic demand, travel constraints, and vehicle capacity limitations.

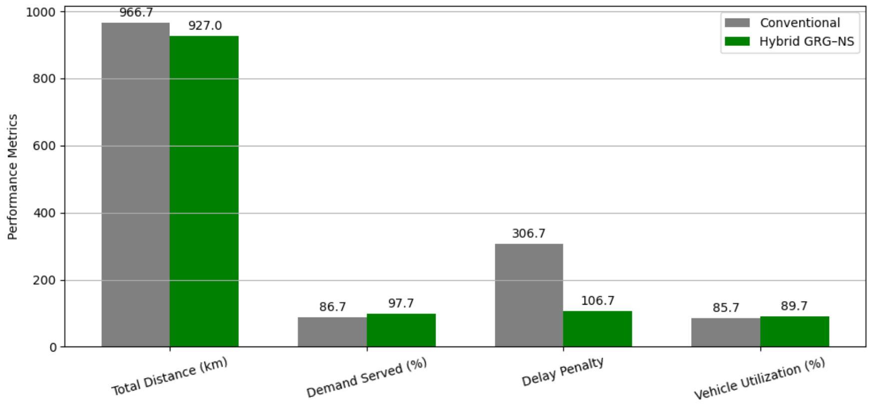


Figure 5. Bar Chart Comparison: Conventional vs. Hybrid GRG–NS

Figure 5 presents a comparative bar chart illustrating the performance differences between the conventional vehicle routing model and the proposed Hybrid GRG–NS model across four key logistics metrics. These include: total distance traveled (km), percentage of demand served, delay penalty, and vehicle utilization.

The Hybrid GRG–NS model consistently outperforms the conventional model across all metrics. In terms of total distance, the hybrid model reduces travel requirements from 966.7 km to 927.0 km, indicating a more efficient route structure. The demand fulfillment rate increases notably from 86.7% to 97.7%, highlighting the hybrid model's capability to adaptively allocate resources and meet delivery needs under dynamic conditions. Additionally, delay penalties—which are critical in disaster logistics are significantly reduced from 306.7 to 106.7, showing a 65% improvement in timeliness and schedule adherence. Lastly, vehicle utilization improves from 85.7% to 89.7%, suggesting that the hybrid model ensures better fleet management and operational efficiency. However, applying the model to larger networks with more depots, vehicles, and customers may pose scalability challenges due to increased computational complexity. To address these challenges, strategies such as hierarchical clustering, parallel computation, and heuristic initialization can be employed to maintain efficiency. These considerations highlight the model's applicability and provide guidance for extending it to real-world, large-scale disaster logistics scenarios.

While the current simulations were conducted using three representative scenarios, we recognize that real-world disaster logistics may involve more complex and diverse conditions. Future work should include stress-testing with multiple simultaneous disruptions, variations in fleet size, and additional operational constraints to fully evaluate the robustness and adaptability of the GRG–NS model under challenging disaster environments. These extensions will provide a more comprehensive assessment of the model's applicability in large-scale and highly dynamic logistics operations.

4.3. Discussion

The comparative analysis between the conventional routing model and the proposed Hybrid GRG–NS model reveals substantial improvements in disaster logistics efficiency, particularly in multi-depot and time-sensitive scenarios. The hybrid approach addresses the limitations of static routing by integrating GRG optimization with a NS refinement layer, enabling more dynamic and adaptive routing decisions. From the simulation results, it is evident that the Hybrid GRG–NS model reduces overall travel distance while increasing the proportion of demand served. This is particularly critical in disaster contexts, where rapid and complete fulfillment of aid delivery can directly impact survival rates and post-crisis stabilization. The observed reduction in delay penalties further illustrates the hybrid model's ability to schedule routes more effectively, avoiding peak delays or routing bottlenecks, especially in disrupted zones with altered travel times.

Moreover, the visual evidence from figure 3, figure 4 and figure 5 supports the numerical findings. The optimized network graph eliminates redundant connections and prioritizes the shortest, feasible, and high-demand paths from the available depots to critical customer nodes. These improvements are not only algorithmic in nature but also operationally significant supporting better vehicle allocation, higher delivery success rates, and reduced logistical costs. Another key observation is the increased vehicle utilization under the hybrid model, implying that fewer vehicles are left idle, and resources are used more effectively. This advantage is highly relevant when vehicle availability is constrained, such as during large-scale disaster response operations.

Overall, the hybrid model demonstrates its strength in handling nonlinear constraints, dynamic demands, and real-time routing adjustments. It successfully transitions from a theoretical mathematical formulation into a practical decision-support tool for emergency logistics. The consistency between visual, numerical, and comparative metrics confirms the robustness and scalability of the proposed approach.

5. Conclusion

This study presents a novel Hybrid GRG–NS optimization model tailored for dynamic multi-depot vehicle routing problems under disaster conditions. Through rigorous formulation and scenario-based simulation, the model proves superior to conventional heuristics by significantly improving delivery performance across multiple metrics: reduced distance, higher demand fulfillment, minimized delay penalties, and better fleet utilization. These results validate the feasibility of using GRG for nonlinear constraint resolution and NS for adaptive routing refinement. The approach offers a solid decision-support tool for emergency logistics and opens opportunities for future enhancement using deep learning for real-time demand forecasting. For future work, the integration of deep learning techniques, such as LSTM-based demand forecasting, could be incorporated as an upstream module to provide predicted customer demand and dynamic time window information. The GRG–NS optimization model would then use these forecasts as input, allowing routes and vehicle assignments to be adjusted proactively in response to anticipated demand variations. This approach would enhance the model's adaptability and decision-making under dynamic disaster logistics conditions.

6. Declarations

6.1. Author Contributions

Conceptualization: D.H., P., L.T.; Methodology: D.H., L.T.; Software: D.H.; Validation: P., L.T.; Formal Analysis: D.H.; Investigation: D.H.; Resources: P., L.T.; Data Curation: D.H.; Writing – Original Draft Preparation: D.H.; Writing – Review and Editing: P., L.T.; Visualization: D.H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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